Using Earth Observations to Understand and Predict Infectious Diseases

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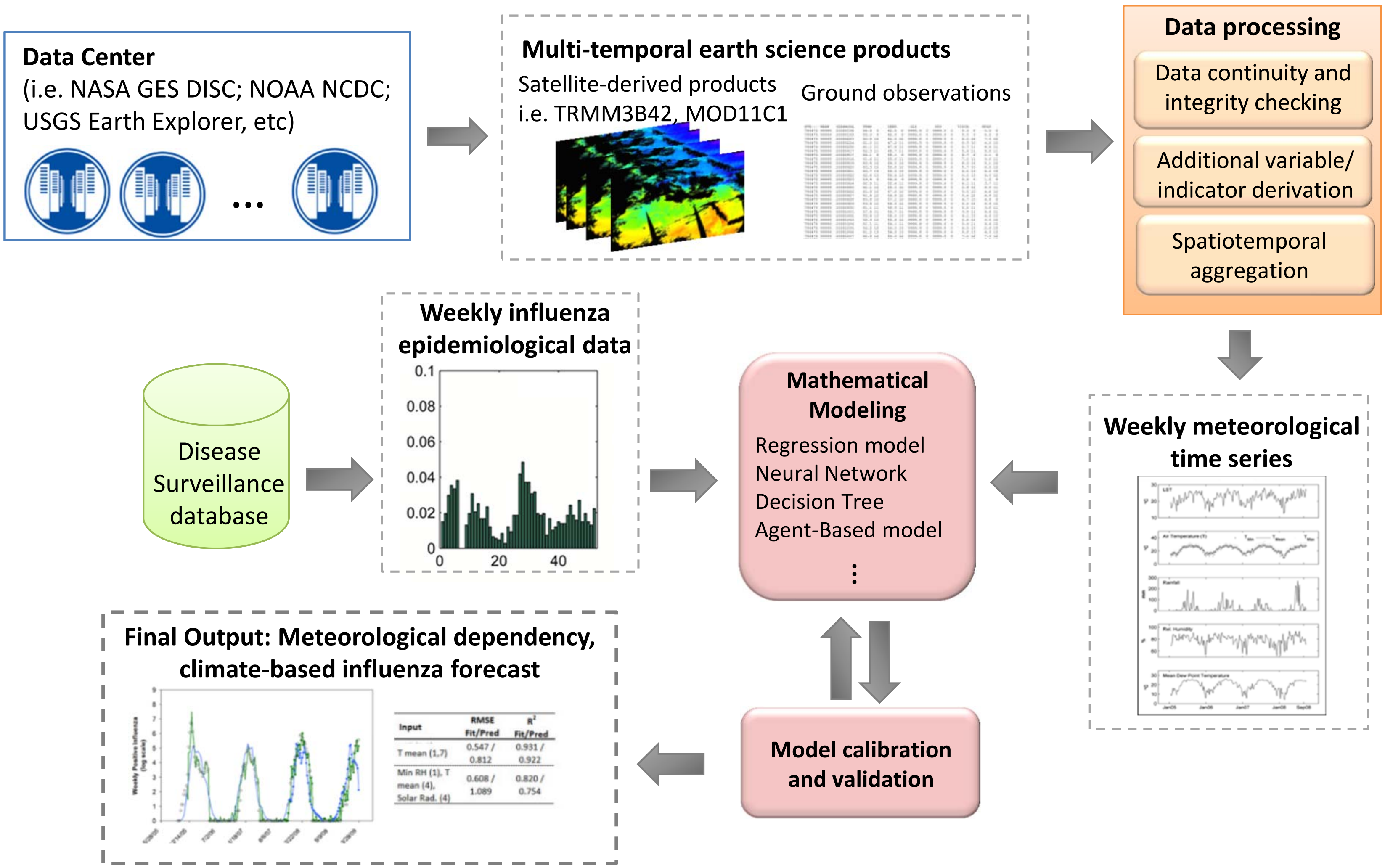
Objective

- Characterize relationship between disease outbreaks and environmental, meteorological parameters
- Use the relationship to forecast disease outbreaks
- Disease applications:
  - Seasonal and pandemic influenza, malaria, dengue

Schematic Approach



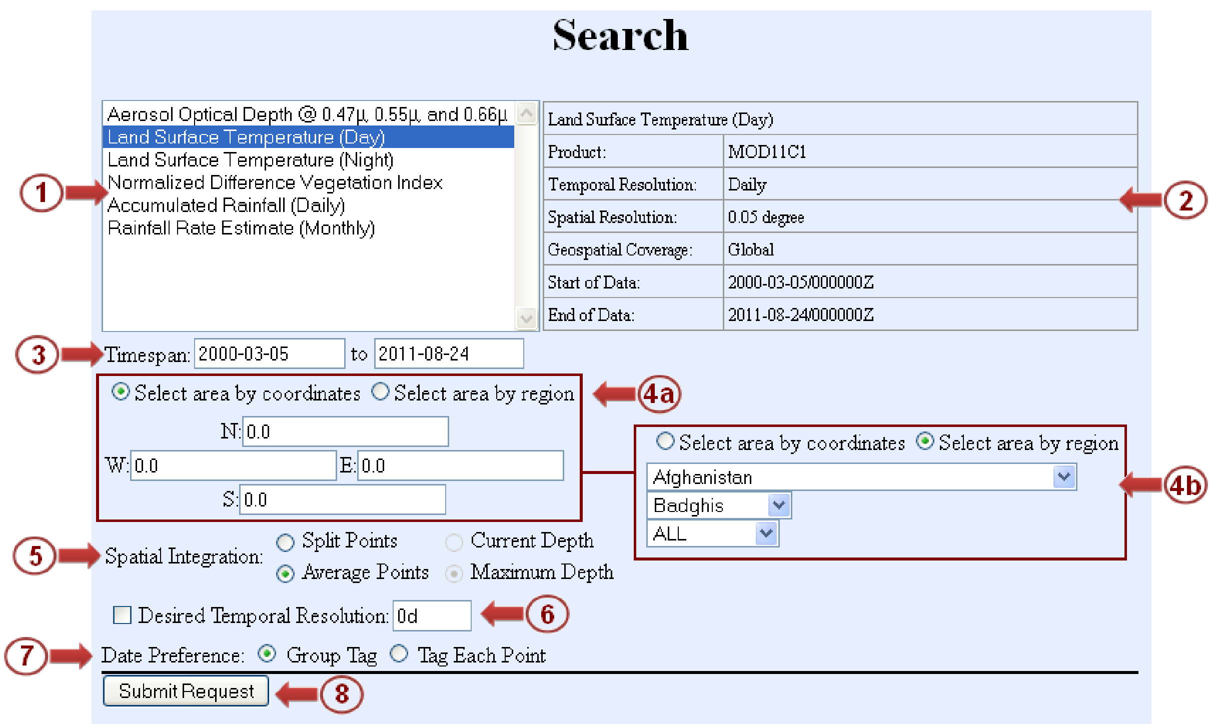
Meteorological Data Processing

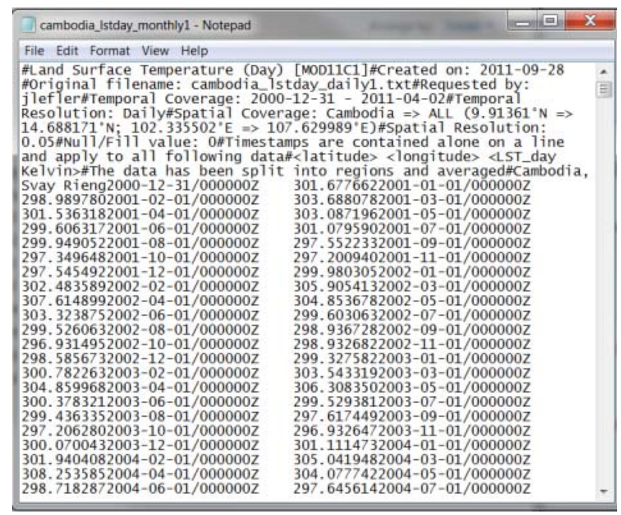
- Epidemiological and virological surveillance data are typically aggregated
  - Spatially: district, provincial or national level
  - Temporally: weekly or monthly
- Satellite data processing
  - Projection; masking region of interest; spatial and temporal averaging; data imputation
- Ground station processing
  - Spatial and temporal averaging; data imputation
- Create lag variables

Meteorological Data Processing

Internal database of satellite data for epidemiological analysis

- Six satellite data products
- Spatial and temporal aggregation capabilities





Influenza: The Problem

Latitudinal variation of seasonal influenza epidemics

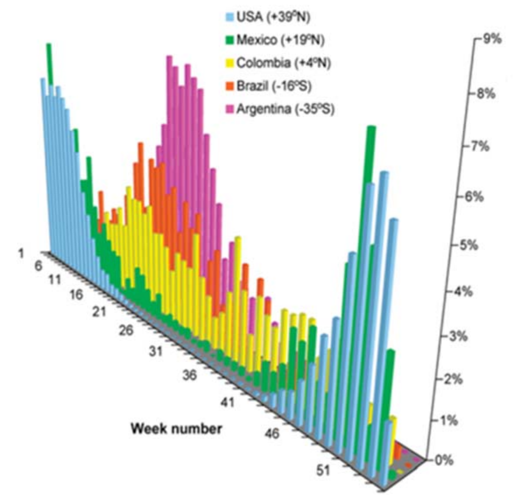
- Temperate region: distinct annual peak in winter
- Tropical region: less distinct seasonality, multiple peaks

Southward migration in Brazil

- From low population in the tropics to dense area with temperate climate

Suggest the role/influence of environmental and meteorological factors

- Several meteorological parameters has been implicated in influenza outbreaks
- Temperate region: low temperature and humidity
- Tropical region: rainfall in several countries



Viboud et al. (2006).
PLoS Medicine 3:e89

Virus Survival	Temperature	↓
	Humidity	↓
	Solar Irradiance	↓
Transmission	Temperature	↓
	Humidity	↓
	Vapor Pressure	↓
	Rainfall	↑
	ENSO	↑
	Holidays	↑
Host Susceptibility	Sunlight	↓
	Nutrition	↕

Example: Influenza In Central America

Soebiyanto RP, Clara W, Jara J, Castillo L, et al. (2014) The Role of Temperature and Humidity on Seasonal Influenza in Tropical Areas: Guatemala, El Salvador and Panama, 2008–2013. PLoS ONE 9(6): e100659.

Meteorological Data

Data Source

– Tropical Rainfall Measuring Mission (TRMM): Daily resolution at 0.25° (~ 25 km)

– Global Land Data Assimilation System (GLDAS): 3-hourly resolution at 0.25° (~ 25 km)

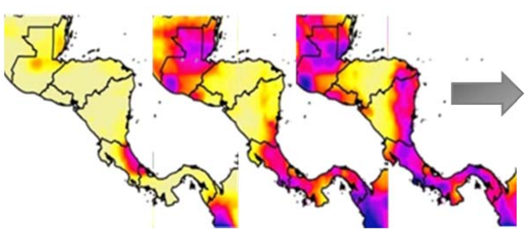
Precipitation: TRMM

Near Surface Temperature: GLDAS

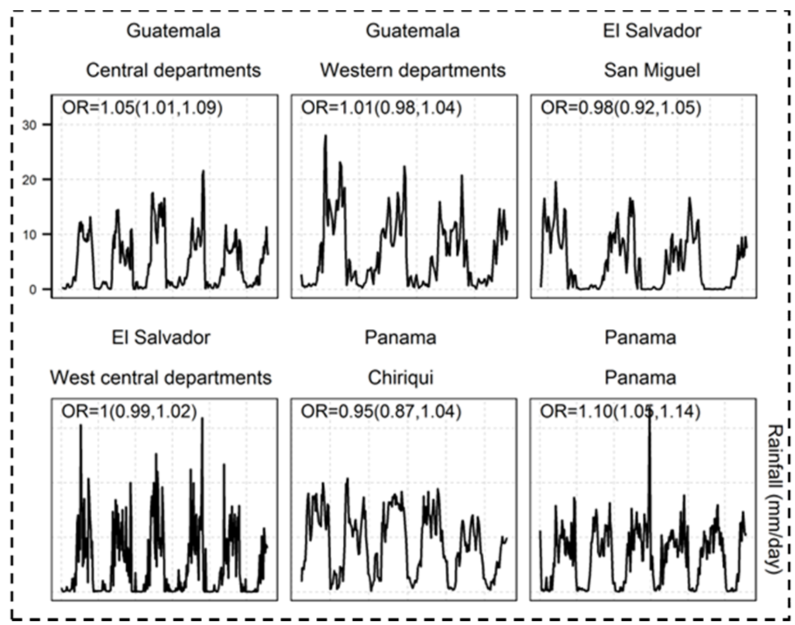
Near Surface Specific Humidity: GLDAS

Meteorological data processing

Multi-temporal (daily) precipitation rate (TRMM) from Giovanni



Spatio-temporal aggregation



Regression Modeling

Logistic regression

$$Y_{kt} \sim Bin\ (N_{kt},\ p_{kt})$$

$\boldsymbol{Y_{kt}}$ is the number of samples tested positive for influenza virus in location *k* at week *t;*
$\boldsymbol{N_{kt}}$ is the total samples collected/processed from location *k* at week *t;* $\boldsymbol{p_{kt}}$ is Y_{kt} / N_{kt}

The logit of influenza positive proportion is defined as:

$$z_{kt} = \ln\left(\frac{p_{kt}}{1 - p_{kt}}\right)$$

The full model can be written as:

Regression coefficients to be estimated

$$z_{kt} = \alpha + \sum_{j=1}^{3} \beta_{jk} x_{jkt} + \sum_{l=1}^{3} \gamma_{lk} v_{lkt} + \sum_{m=1}^{4} \lambda_{mk} z_{k(t-m)} + \sum_{n=1}^{3} \theta_{nk} w_{kt}^{n}$$

Meteorological variable
(i.e. temperature, humidity, rainfall)

Co-circulating viruses (RSV,
adenoviruses) as confounding factor

Previous weeks
influenza activity

Polynomial function of
week number

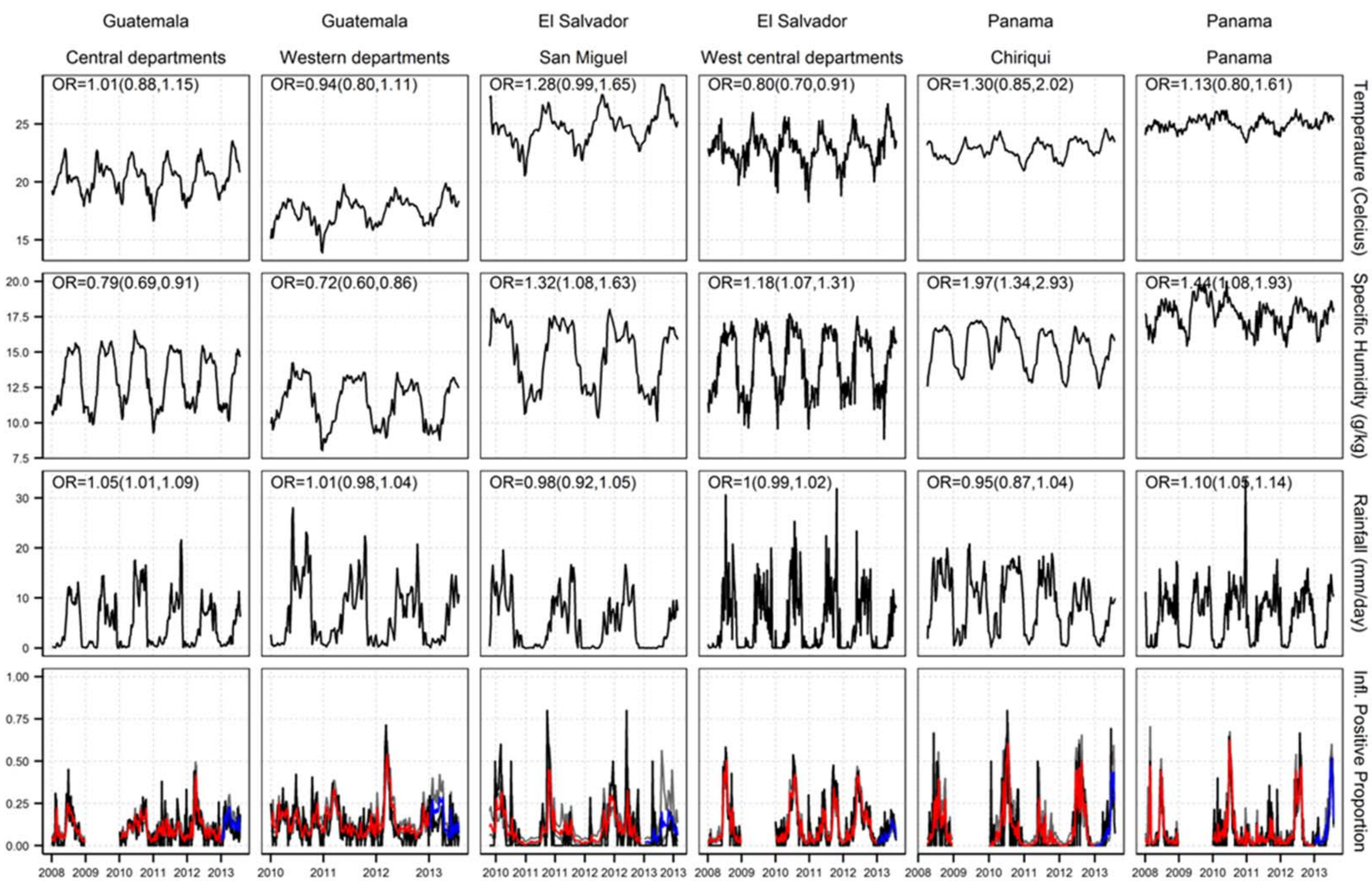
Results: Estimated Coefficients

Country and Province	Adjusted Odds Ratio (95% Confidence Interval)			Meteorological Variable Average Period	Prediction	
	Temperature (°C)	Specific Humidity (g/kg)	Rainfall (mm/day)		RMSE	Corr. Coeff
Guatemala						
Central departments	1.01 (0.88, 1.15)	**0.79 (0.69, 0.91)**	**1.05 (1.01, 1.09)**	Prev. 1–3 wks ave.	0.08	0.12
Western departments	0.94 (0.80, 1.11)	**0.72 (0.60, 0.86)**	1.01 (0.98, 1.04)	Prev. 0–1 wks ave.	0.13	0.08
El Salvador						
West-central departments	**0.80 (0.70, 0.91)**	**1.18 (1.07, 1.31)**	1.00 (0.99, 1.02)	Prev. 1 wk ave.	0.06	0.50
San Miguel	1.28 (0.99, 1.65)	**1.32 (1.08, 1.63)**	0.98 (0.92, 1.05)	Prev. 1–2 wks ave.	0.13	0.02
Panama						
Chiriquí	1.30 (0.85, 2.02)	**1.97 (1.34, 2.93)**	0.95 (0.87, 1.04)	Prev. 0–3 wks ave.	0.11	0.73
Panama	1.13 (0.80, 1.61)	**1.44 (1.08, 1.93)**	**1.10 (1.05, 1.14)**	Prev. 1–2 wks ave.	0.07	0.90

Bold font indicates a statistically significant variable (*p-value*$<$0.05). RMSE is the Root Mean Squared Error and Corr. Coeff is the correlation coefficient between the observation and estimated influenza positive proportion in 2013.
The models were adjusted for: potentially confounding variables (RSV, parainfluenza and adeno viruses), previous weeks' influenza positivity, seasonality and other possible nonlinear relationships (modeled as a polynomial function, up to degree of 3, of the week number).
doi:10.1371/journal.pone.0100659.t002

Specific humidity was consistently associated with influenza activity in all study locations with **bimodal** relationship:
Proportional relationship in Guatemala and **invers**e relationship in other locations

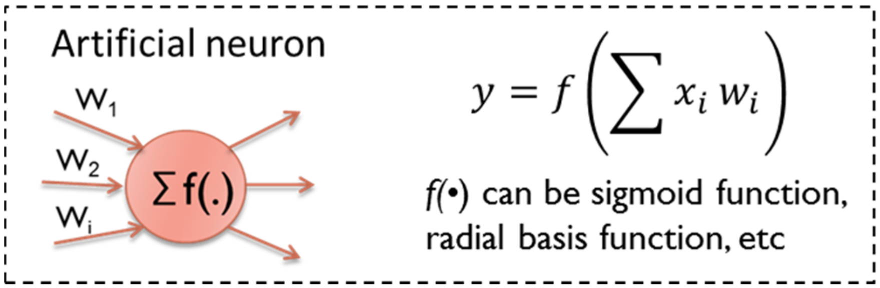
Results: Training and Prediction

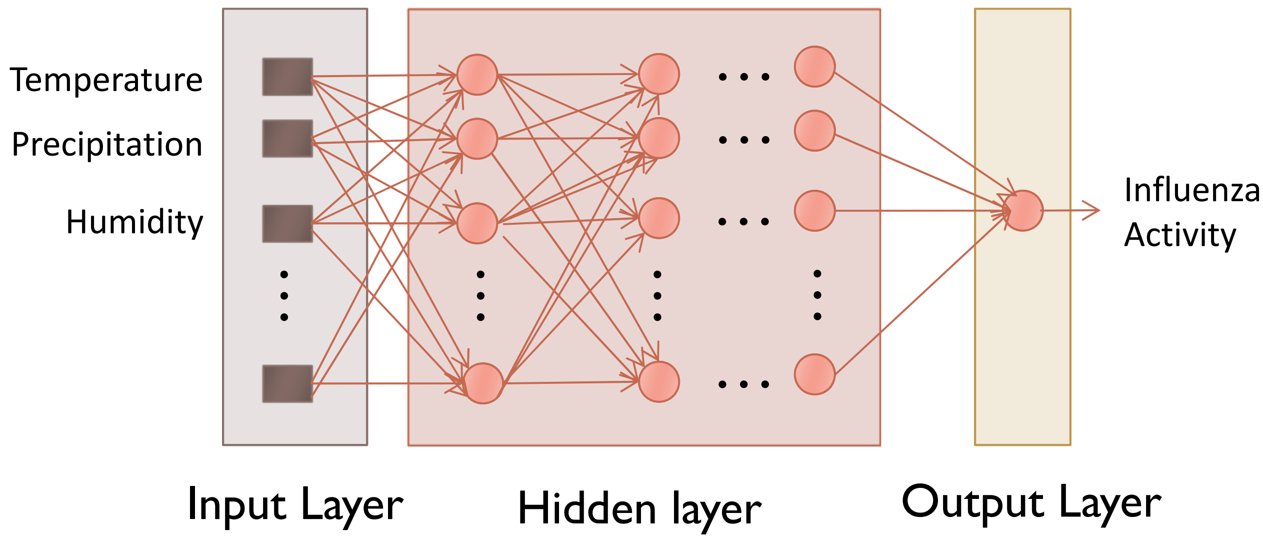


— Modeled training data — Prediction — Observation

Neural Network

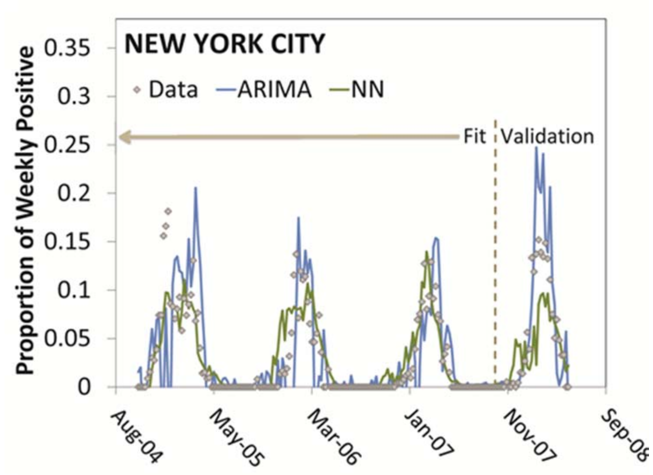
Artificial intelligence method that mimic the functioning of the brain

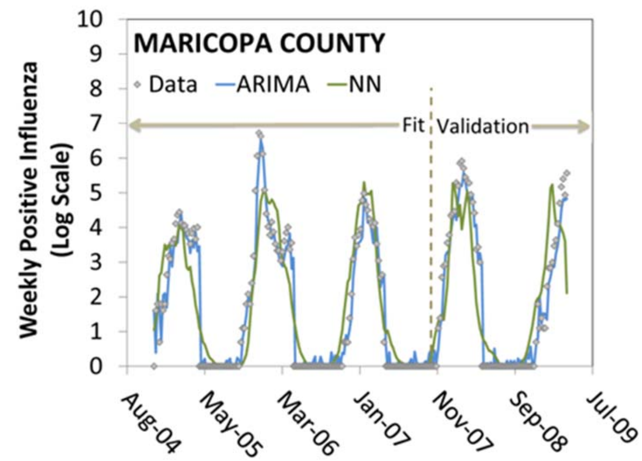




Neural Network Example

Neural Network (NN) and ARIMA outputs for New York City and Maricopa County (AZ)





	Input	RMSE (Fit/Pred)	R^2 (Fit/Pred)
ARIMA	Mean Dew Pt (4)	0.046/0.022	0.311/0.795
NN	TMAX (1), Rain (3), TMIN (2)	0.044/0.0036	0.731/0.584

	Input	RMSE (Fit/Pred)	R^2 (Fit/Pred)
ARIMA	RHMAX (3), LST(3)	0.575/0.5493	0.911/0.941
NN	RHMIN(1), TEMP(4), SOLAR(4)	0.608/1.089	0.820/0.754

NN model shows that ~60% of influenza variability in the US regions can be accounted by meteorological factors

Summary: Challenges

Meteorological Data and Processing

- Changes in or heterogeneity of: location, formats, algorithm, availability (data continuity)
- Storage capacity
- Data products validation

Uncovering patterns & modeling

- Choice of mathematical and statistical models
- Each model has assumptions such that results and prediction may need to be appropriately interpreted
- Parameter constraints and prediction validation

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